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Regression Neural Network Approach on Cutting Parameters in AWJM Process for Various Alloys

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The development of high-strength alloys, such as nonferrous alloys, has been driven by advancements in metallurgy and the increasing demand for robust materials across various industries. These alloys, however, pose significant challenges when machined using traditional methods. Conventional machining often leads to damage of both the workpiece and the tool due to the physical removal of material using a sharp cutting tool. In contrast, Non-Traditional Machining (NTM) processes remove material through the application of thermal, chemical, or electrical energy, or a combination of these energies, making them better suited for hard and brittle materials. Among the non-traditional techniques, Abrasive Water Jet Machining (AWJM) stands out for its flexibility and precise control over process parameters. This study employs a combination of experimental observations, multiple regression modeling, and Regression Neural Networks (RNN) to optimize AWJM process parameters for machining Aluminium 6061 alloy, Copper-Iron alloy, and Lead-Tin alloy. The findings indicate that the G method effectively determines the optimal AWJM process settings for these alloys.

Keywords: High-Strength Alloys, Non-Traditional Machining, Abrasive Water Jet Machining (AWJM), Regression Neural Networks, Process Optimization.

1. Introduction

WJC machines commence to function in the early 1970s to cut wood and plastics material proposed by Kovacevic. R. [1] and cutting by AWJ was initially commercialized in the late 1980s as a pioneering step forward in the NTM technologies area by Chithirai Pon Selvan. M [2]. In the early 1980s, AWJM has preferred as an impractical application. Today, state of the art abrasive jet technology was brought up into a production process of full scale with steady and persistent outcome proposed by Adnan Akkurt [3]. In AWJM process, removal of the work piece material is by the high velocity jet of water action assorted with particles that are abrasive depending upon the material erosion principle upon which gets hit by the water jet by Metin Kok [4]. AWJM is one of the highly superior recent techniques utilized in manufacturing industry for processing of material. AWJM exhibits little benefits namely less cutting forces, exclusive versatility in machining, superior flexibility and no thermal distortion probsed by Caydas Ulas., and Ahmet Hascalik [5]. Assessing against other corresponding process of machining, no Heat Affected Zone (HAZ) on the work piece is generated by Bostjan Jurisevic [6].

Srinivasu. D.S. and Ramesh Babu. N. [7] developed a machine vision dependant technique to monitor and get hold of the bore diameter of the nozzle which has been focused from time to time and a neuro genetic technique has been engaged as a strategy for controlling and for modifying the parameters of process. On combination the strategies to control and monitor, an integrated technique to control adaptive of AWJC process has been recognized. Przemyslaw. J. and Borkowski [8] showed a narrative technique for the 3D sculpturing of various materials utilizing a high pressure AWJ and this deals with scanning an image, such as a photograph, and associating the values of color of each pixel in the consequential bitmap image to the water jet feed rate. Holding every other parameters namely water pressure constant and SOD, various water jet feed rates would end up in material's dissimilar erosion levels. As a consequence, a 3D sculptured surface would be recognized from a 2D image. The work presented a systematic and investigational erosion ends up together with a specific example of bas relief from metal. Mahabalesh Palleda [9] presented the influence of utilizing dissimilar chemicals on MRR, with diverse SODs and concentration of chemical in AWJM and usage of those chemicals on the taperness of drilled holes has also been learnt and this investigation discloses that the usage of polymer could decline the drilled holes taper. Hassan. A.I. and Kosmol. J. [10] developed the academic and experimental models that were brought up for AWJM, the specific nature of erosion hasn't been understood yet. This work contributes an attempt for modeling AWJM involving the Finite Element Method (FEM) in the idea of explaining the abrasive particle work piece process of interaction. Finally, the present FEM results are consistent with experimental results. Paul. S. [11] illustrated, in the AWJM of brittle materials, the stress wave energy, related with the abrasive particles impact, contributes as a significant factor in removal of material by fracture. The models which are availably currently are idealized and modified and won't take into account the shape or size of the particle. The work deals with the issue of considering the particles size and shape. The outcomes symbolize that utilization of spherical blunt particles in the AWJM of brittle materials will show the way to more fracture.

Wang.J. and Wong. W.C.K. [12] presented AWJC of metallic coated sheet steels on a statistically DOE. AWJC is a feasible technique to process metallic coated sheet steels with better productivity and kerf quality. Chithirai Pon Selvan. M. and Mohana Sundara Raju. N [13] illustrated AWJC is better to few other cutting techniques to process range of materials, specifically complicated to cut materials. In this work, a set of experimental data was utilized in assessing the authority of AWJC parameters of process in cutting of Aluminium. Experiments have been performed in varying the AFR, traverse speed, water pressure and SOD to cut Aluminium utilizing AWJC process. Study was performed on the influence of pressure and traverse speed on DOC. Using regression analysis, a predictive model for the DOC in AWJC process of Aluminium is then developed and verified. Model verification for utilizing it as a sensible guideline which was identified for agreeing along the experiments. Limbachiya [14] described AWJM is a NTM process. On a work piece AWJM is a technique for material removal by impact erosion of high pressure (1500-4000bar), entrained high velocity, high velocity of water of grit abrasives. It's a UCM process. At first this targets on theoretical work later on it create few experimental work and analyzing of both outcomes have been done. Theoretical MRR identified to be equal to the experimental MRR. For three dissimilar materials like Acrylic, Aluminium and EN8 has been implemented involving Taguchi DOE method. Experiments were performed in L_{25} orthogonal array by changeable material traverse speed and mass flow rate of abrasive for every material and ANOVA is executed for identifying significant parameters.

Adel.A. Abdel-Rahman [15] developed an elastic plastic erosion model that has been adopted for developing an AWJ model to cut materials that are brittle. As an outcome, a cutting model that is in closed form is dependent on fracture mechanics that has been derived and commenced. The recommended model forecasts the highest DOC of the intended material as a purpose of the toughness and hardness of fracture, together with parameters of process. The utmost DOC forecasted by the recommended model has been assessed with published investigational outcome for AD99.5 ceramic material. The control of parameters of the process in utmost DOC for AD99.5 ceramic material has also been researched and weighed against with investigational task. The assessment makes known that better understanding among the model forecasting and investigational outcomes exist, where the dissimilarity among the forecasted and investigational values of the utmost DOC was identified for taking a value in average of 3.9%.The forecasted DOC of the current model for 7 dissimilar ceramic materials has been assessed with that by a preceding model, where the both models have been identified for forecasting the similar kind of utmost depth of cut within an average value of 4%.

Ma.C. and Deam. R.T. [16] investigated AWJC could generate tapered edges on the kerf of work piece which is cut and this could restrict the competent applications of AWJC, for the part when additional machining over edges is required for achieving engineering tolerance necessary. Measurement for the kerf geometry was done involving an optical microscope in this research and with those measured values, a basic empirical association for the kerf profile shape beneath dissimilar traverse speed has been brought up fitting much the shape of kerf.

Farhad Kolahan and Hamid Khajavi. A. [17] investigated a cumbersome of experimental data was utilized for weighing the effect of AWJ parameters of process to cut 6063 T6 Aluminium alloy. Variables of the process preferred at this point comprise nozzle diameter, jet pressure, jet traverse rate and AFR. Influence of these input parameters have been researched on DOC (h); one of the highly significant characteristics of AWJ. Regression modeling and Taguchi method have been utilized in the idea of presenting relationships among input and output parameters. ANOVA technique assesses the sufficiency of the model. Projected model is entrenched into a Simulated Annealing (SA) algorithm for optimizing AWJ process parameters in later stage. Purpose for resolving an appropriate group of parameters of process could generate a preferred DOC, preferring the ranges of parameters of the process. Computational outcomes confirm efficiency of the projected model and procedure to optimize.

Jiyue Zeng and Thomas. J. Kim [18] investigate the phenomenon of erosion connected with AWJC of polycrystalline ceramics. Mechanism of erosion has been monitored here comprise inter granular network cracking and plastic flow. Removal of material because of cracking of network has been considered with a crack network model that associates the surface energy of fracture in creating the crack network to the energy of the impact induced stress waves. Involvement of plastic flow has been assessed with Finnie's model. The model of derived has been confirmed with experiments of AWJ erosion.

The literature survey made for this research work revealed that the researchers conducted on AWJM are related to recent trends in AWJM, different materials and effects of process parameters on MRR, SR and Kerf and also optimization/prediction using modeling of soft computing approaches. It is also inferred that more research involving number of process parameters are to be done in this area. The literature survey helped to successfully design, construct, and conduct the experimentation, modeling and performance evaluation of this research work.

2. Data Collection and Experimentation

The experimental design and investigation methodology is very important in maintaining the reliability of entire research work. It is useful for fixing the level of experiments, conducting experiments, recording the experimental results, evaluating the results and analysis of the results. The methodology for the present work has been designed effectively to conduct numerous experiments to study the entire spectrum of levels of AWJM process parameters for maximum MRR and minimize SR on nonferrous metals and its alloys. The reduction in number of experiments greatly reduces the time and the cost. To understand the cause of each AWJM parameters on response MRR and SR and to identify the significant parameters, experiments need to be conducted by varying the level of each parameter one at a time. This proves very cumbersome as the number of experiments to be conducted increases exponentially with the number of process parameters. Hence, it's highly difficult to draw any conclusion with minimum number of experiments in this approach. Thus, well scheduled set of experiments, where all parameters are varied with specified range, is a better approach for obtaining systematic data.

Performing the experiments on the sub set of complete set of experiments makes the experimentation process quick and cost effective. The RSM using the Box-Behnken design is highly effective in identifying the sub set of experiments to be done to study the complete range and combination of process parameters in minimal number of experiments. Thus, RSM is used to select optimum levels of process parameters and number of experiments required to ensure the quality of experimentation. Employing this statistical method to design the experiments and analyze the result sets enables the researcher to locate the optimal levels of process parameters. Estimation of the experimental error greatly helps to improve the quality of experiments conducted on Aluminium 6061, Copper Iron and Lead Tin Alloys. The close up view of block used for cutting the specimens which is mounted on the AWJM for all the three materials is shown in Figure 1. The Composition of the three alloys is shown in Table 1.

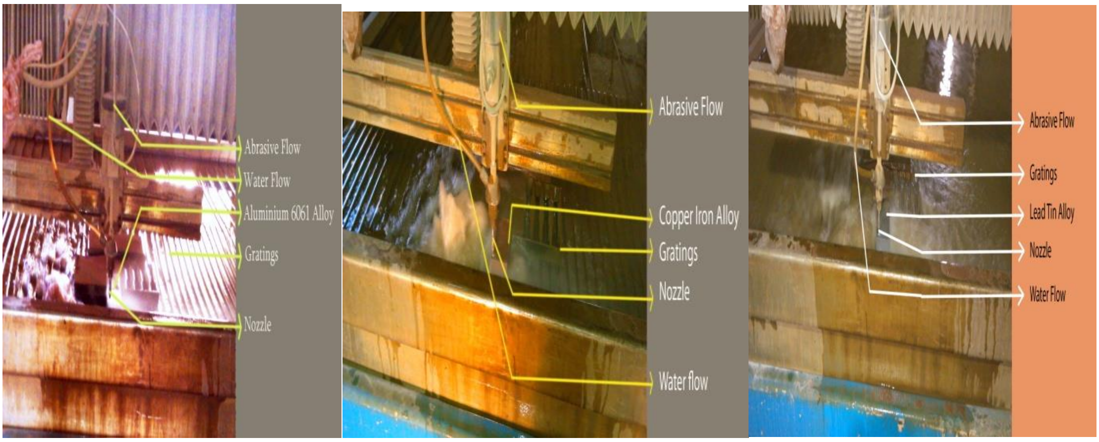

Figure 1: Aluminium 6061, Copper Iron and Lead Tin Alloys Mounted on AWJM

Table 1: Composition of Work Materials

Aluminium 6061 Alloy		Copper Iron Alloy		Lead Tin Alloy	
Elements	Composition	Elements	Composition	Elements	Composition
Aluminium	97.9 %	Copper	96 %	Lead	95 %
Magnesium	1 %	Iron	4 %	Tin	5 %
Silicon	0.6 %	--	--	--	--
Copper	0.28 %	--	--	--	--
Manganese	0.08 %	--	--	--	--
Zinc	0.07 %	--	--	--	--
Titanium	0.066 %	--	--	--	--
Chromium	0.04 %	--	--	--	--

A representative graph of pressure vs output parameters is shown. Similar graphs can be plotted for various output by taking other parameters also in the x axis. Anyhow it won't give any further details. In the optimization techniques the influence of this parameters will be taken care off. That's why the graphs are not plotted for other parameters in the x axis.

a. For a particular thickness of the Al, Cu and Pb alloys (50mm) graphs are plotted between MRR vs. Pressure and SR vs. Pressure for a varying AFR of 0.4kg/min, 0.55kg/min and 0.7kg/min.

b. For a particular thickness of the Al, Cu and Pb alloys (50mm) graphs are plotted between MRR vs. Pressure and SR vs. Pressure for a varying Orifice diameter of 0.3mm, 0.33mm and 0.35mm.

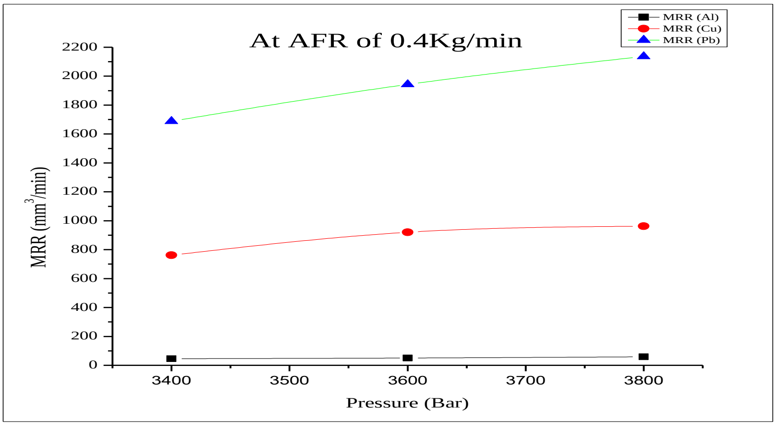

Figure 2: MRR vs Pressure at AFR of 0.4Kg/min

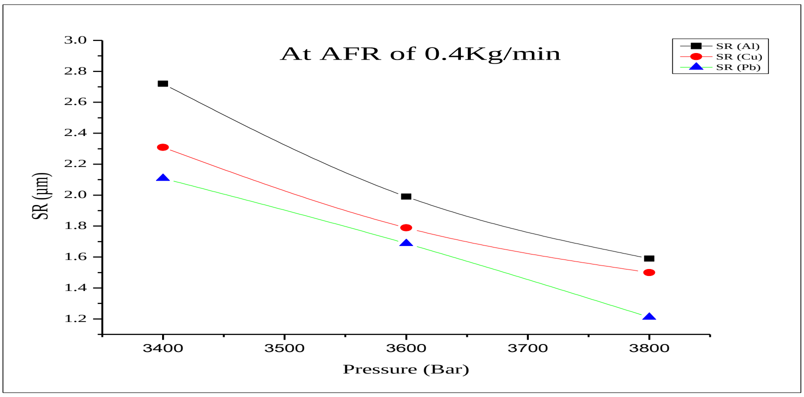

Figure 3: SR vs Pressure at AFR of 0.4Kg/min

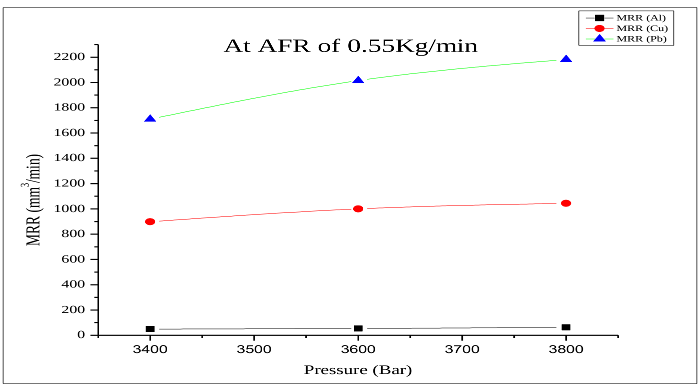

Figure 4: MRR vs Pressure at AFR of 0.55Kg/min

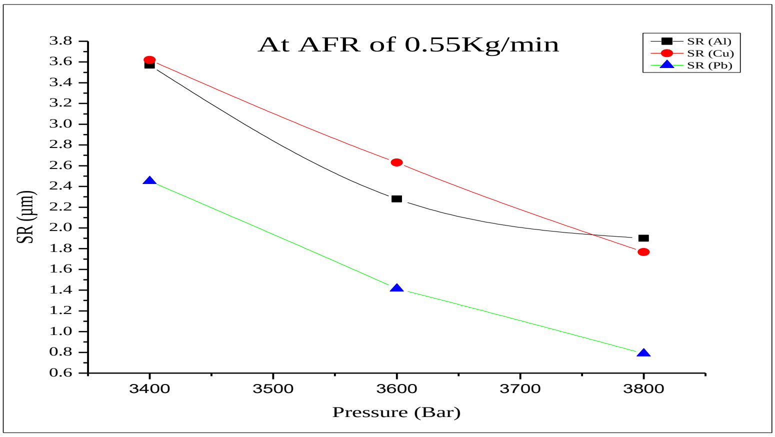

Figure 5: SR vs Pressure at AFR of 0.55Kg/min

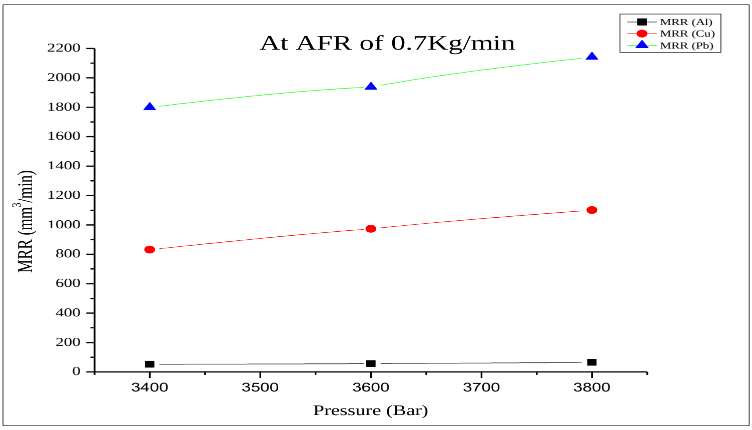

Figure 6: MRR vs Pressure at AFR of 0.7Kg/min

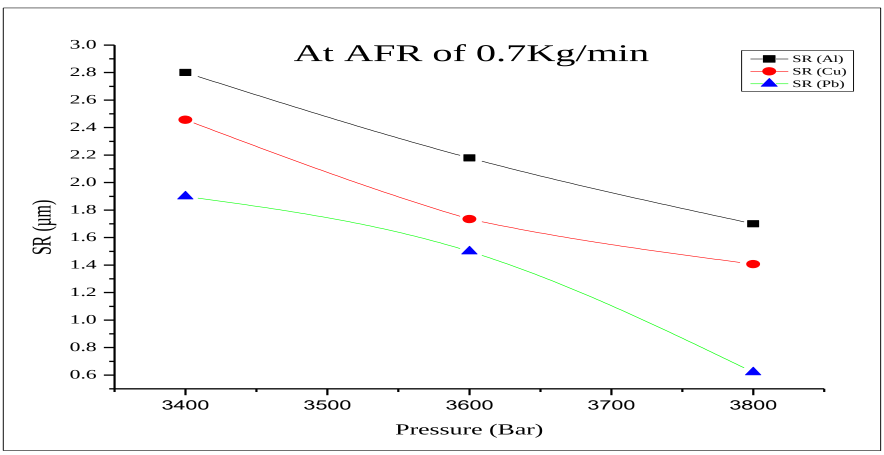

Figure 7: SR vs Pressure at AFR of 0.7Kg/min

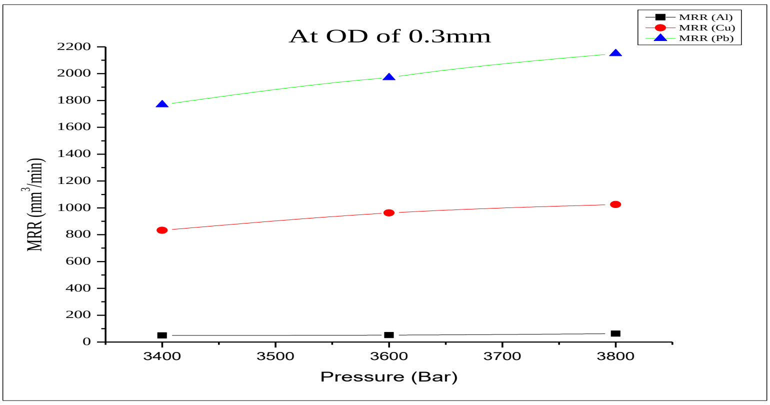

Figure 8: MRR vs Pressure at OD of 0.3mm

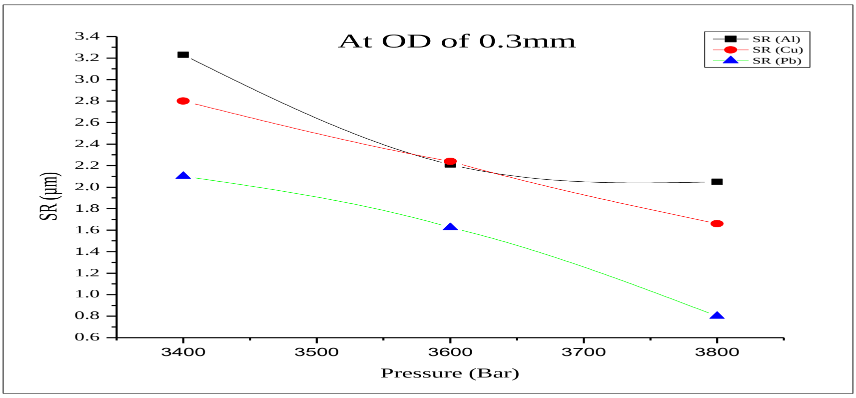

Figure 9: SR vs Pressure at OD of 0.3mm

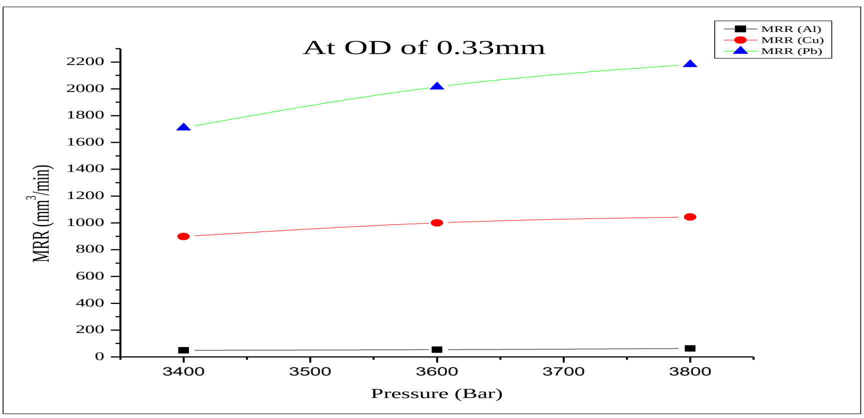

Figure 10: MRR vs Pressure at OD of 0.33mm

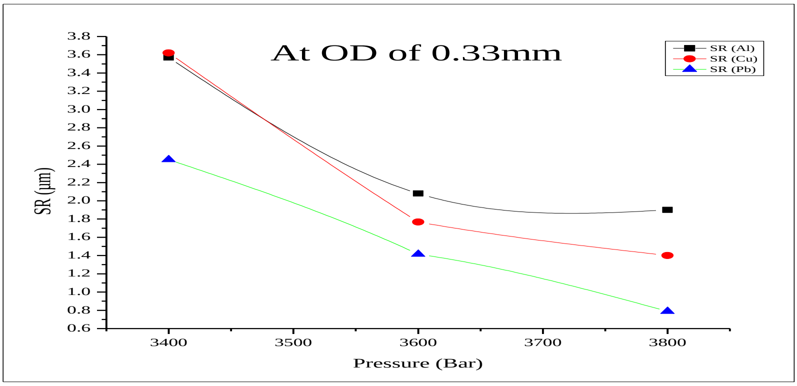

Figure 11: SR vs Pressure at OD of 0.33mm

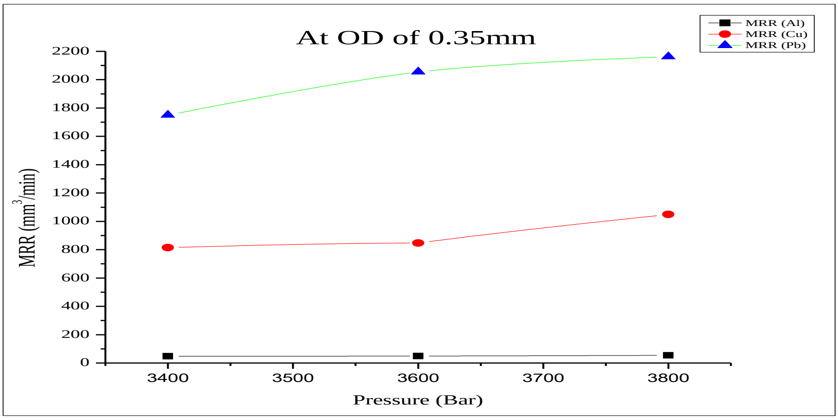

Figure 12: MRR vs Pressure at OD of 0.35mm

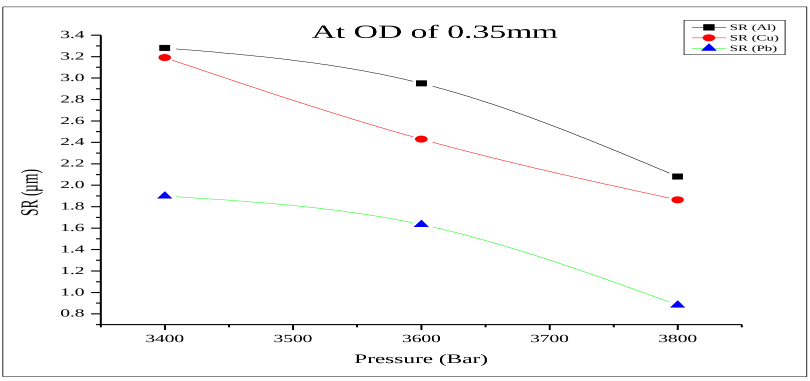

Figure 13: SR vs Pressure at OD of 0.35mm

i) With Abrasive Flow Rate as a Variable

a) The plot between MRR and pressure for increasing AFR in Figures. 2, 4, 6 clearly shows that increasing the AFR, results in increasing the MRR for Aluminium, Copper and Lead alloys.

b) The plot between SR and pressure for increasing AFR in Figures. 3, 5, 7 clearly shows that increasing the AFR, results in decreasing the SR for Aluminium, Copper and Lead alloys.

ii) With Orifice Diameter as a Variable

a) The plot between MRR and pressure for increasing orifice diameter in Figures. 8, 10, 12 clearly shows that increasing the orifice diameter, results in decreasing the MRR for Aluminium, Copper and Lead alloys. This occurs due to the decrease in size of orifice decreases the velocity of AWJ.

b) The plot between SR and pressure for increasing orifice diameter in Figures. 9, 11, 13 clearly shows that increasing the orifice diameter, results in increasing the SR for Aluminium, Copper and Lead alloys. This occurs due to the decrease in size of orifice decreases the velocity of AWJ.

3. RNN Approach to Predict the MRR and SR on Aluminium 6061, Copper Iron and Lead Tin Alloys

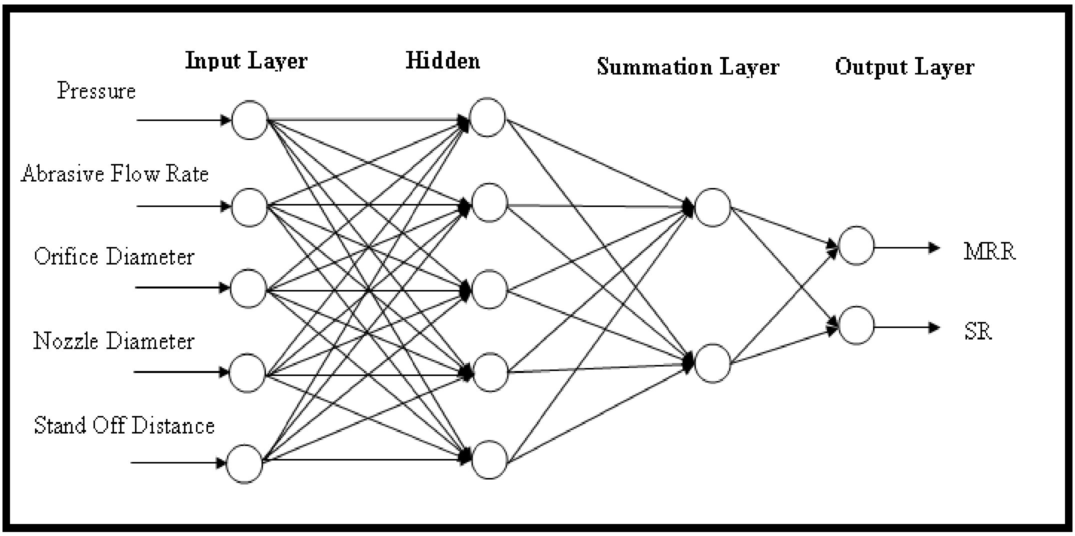

Figure 14: Proposed Architecture of G

In this work, the accuracy of the G model in predicting MRR and SR was investigated and the results were compared with the experimental results. 46 set of data under AWJM process was used for training and testing of the G. Out of 46 experimental data, 23 training data are considered on MRR and SR for the three alloys and 23 testing data sets outside the training data set are selected for testing the G. The performance of the G is studied with the special attention to their generalization ability and the CPU time. The advantage of G is fast learning as it is a one-pass training algorithm. It does not require an iterative training process. The training time is just the loading time of the training matrix. Also it can work both linear and non-linear data. As the sample size increases, the estimate surface converges to the optimal regression surface. Thus it requires many training samples to span the variation in the data and all these to be stored for the future use. However, there is only one disadvantages that there is no intuitive method for choosing the optimal smoothing factor. The results illustrates that the training data and predicted values have come very close to the experimental values of MRR and SR for all the three alloys. Figure 14 shows the proposed Architecture of G

Table 2: Output Value of MRR and SR Through G for Aluminium 6061 Alloy

Sl.No .	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR(μm)	Predicted SR(μm)	Error SR
1.	48.6111	50.30538	3.485376797	3.57	3.39488	4.90532
2.	53.6399	52.2216	2.644113803	2.08	2.11704	1.78077
3.	51.8519	52.21058	0.691739358	2.21	2.261173	2.31552
4.	50.8352	51.72523	1.750814396	2.55	2.41942	5.12078
5.	62.2222	61.31387	1.459816593	1.9	1.820049	4.20795
6.	51.8519	56.21065	8.406152909	2.19	2.261143	3.24854
7.	45.7516	50.12142	9.551185095	3.2	2.944572	7.98213
8.	53.6399	52.27139	2.55129111	1.8	1.658879	7.84006
9.	61.2423	66.31896	8.289466594	2.07	1.892532	8.57333
10.	62.2222	61.31116	1.464171951	2.05	1.870412	8.76039
11.	51.1696	51.72437	1.084178887	2.54	2.41967	4.7374
12.	47.7164	50.14248	5.084373507	3.08	2.942812	4.45416
13.	50.1792	52.17364	3.974634908	1.99	2.118437	6.45412
14.	52.9101	52.21065	1.321959323	2.17	2.261143	4.20014
15.	54.3901	52.21135	4.005784141	2.08	2.261098	8.70663
16.	51.8519	47.21256	8.947290263	2.79	2.561098	8.20437
17.	48.6111	50.14248	3.150268149	3.3	2.982812	9.61176
18.	52.9101	52.21065	1.321959323	2.19	2.261143	3.24854
19.	47.7164	52.15037	9.292339741	2.36	2.263405	4.09301
20.	48.3092	50.14289	3.79573663	2.95	2.942716	0.24692
21.	58.4785	61.28001	4.790666655	1.89	1.821466	3.62614
22.	54.7731	51.77715	5.469747011	2.25	2.417438	7.44169
23.	56.3607	52.26618	7.264849443	1.68	1.515364	9.79976
24.	49.2264	52.30029	6.244393252	2.29	2.214699	3.28825
25.	48.9168	52.30162	6.919545023	2.36	2.215338	6.12975
26.	51.1696	52.22116	2.05504831	2.5	2.309217	7.63132
27.	55.9552	52.35901	6.426909385	2.14	2.211431	3.3379
28.	49.2264	47.63344	3.235987194	2.65	2.845396	7.37343
29.	56.7721	52.35636	7.778010678	2.18	2.210989	1.42151
30.	50.8352	52.66547	3.600398936	1.9	2.001934	5.36495
31.	51.8519	52.6664	1.57081997	1.99	2.102359	5.64618
32.	64.8148	61.044	5.817807044	1.7	1.865359	9.727
33.	48.6111	52.29841	7.585325162	2.4	2.21441	7.73292
34.	52.1999	57.22006	9.617183175	2.68	2.50935	6.36754
35.	52.9101	52.32855	1.099128522	2.2	2.212847	0.58395
36.	59.8291	61.01913	1.989048807	1.99	1.964843	1.26417

37.	51.8519	47.7287	7.95187833	2.8	3.0180838	7.78871
38.	51.1696	52.32791	2.263668272	2.34	2.212393	5.45329
39.	48.9168	47.71524	2.45633402	3.23	3.181011	1.51669
40.	48.3092	52.19532	8.044264861	2.69	2.810795	4.49052
41.	53.2725	52.32855	1.771927355	2.18	2.212847	1.50674
42.	52.5526	52.66761	0.218847402	1.8	1.962175	9.00972
43.	59.3724	61.02141	2.777401621	1.82	1.964684	7.94967
44.	56.7721	52.35604	7.778574335	2.03	2.21049	8.89113
45.	51.1696	52.221	2.054735624	2.73	2.508869	8.10004
46.	61.2423	60.99504	0.403740552	1.72	1.85198	7.67326

The Table 2 shows the errors between the experimental and predicted values for MRR and SR using G for Aluminium 6061 Alloy. The comparison between the experimental values and predicted values of MRR and SR using G of Aluminium 6061 alloy is shown in Figure 15 and Figure 16.

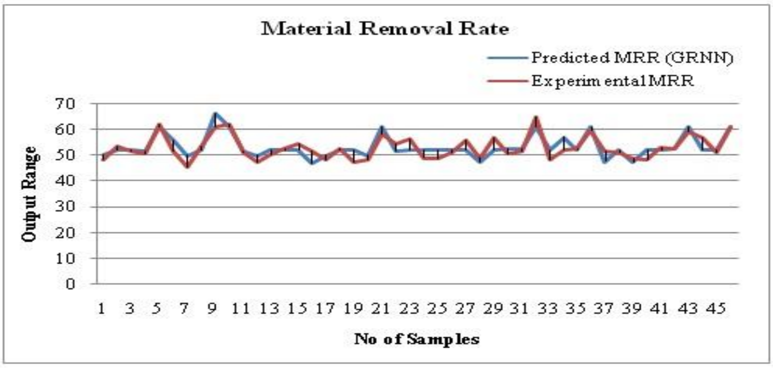

Figure 15: Comparison of Experimental and Predicted MRR for Aluminium 6061 Alloy

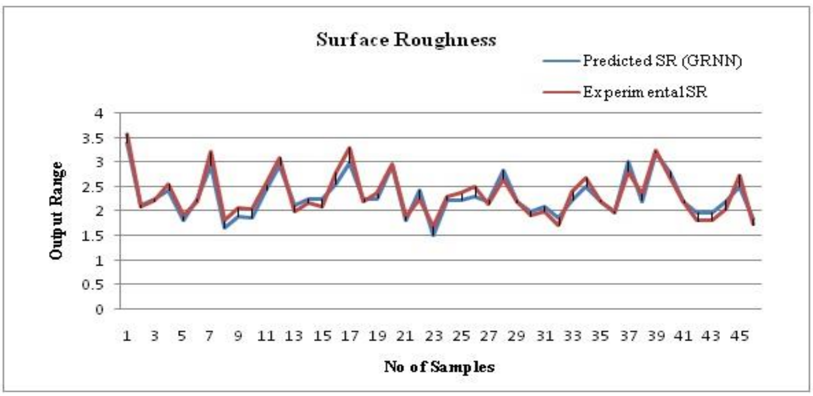

Figure 16: Comparison of Experimental and Predicted SR for Aluminium 6061 Alloy

The Table 3 shows the errors between the experimental and predicted values for MRR and SR using G for Copper Iron Alloy. The comparison between the experimental values and predicted values of MRR and SR using G of Copper Iron alloy is shown in Figure 17 and Figure 18.

Table 3: Output Value of MRR and SR Through G for Copper Iron Alloy

Sl.No.	Experimental MRR (mm^3/min)	Predicted MRR(mm^3/min)	Error MRR	Experimental SR(μm)	Predicted SR(μm)	Error SR
1.	897.8	829.7916	7.575005569	3.62	3.606213	0.38086
2.	1000.03	934.8857	6.514234573	1.63	1.546354	5.13166
3.	961.93	917.6243	4.60591727	2.24	2.328035	3.93013
4.	918.21	909.39	0.960564577	3.09	2.945445	4.67816
5.	1043.96	1072.895	2.771657918	1.767	1.674749	5.22077
6.	928.76	917.626	1.198802705	2.228	2.328133	4.4943
7.	762.29	824.0247	8.098584528	3.309	2.992095	9.57706
8.	985.39	918.6555	6.772394686	2.19	2.321454	6.00247
9.	987.8	1064.94	7.809273132	1.901	1.801852	5.21557
10.	1025.41	1072.821	4.623613969	1.66	1.574658	5.14108
11.	907.89	989.3779	8.975525669	2.77	2.545533	8.1035
12.	800.02	824.1133	3.01158721	2.991	2.850925	4.68322
13.	920.3	934.0995	1.499456699	1.989	2.151262	8.15797
14.	922.4	977.626	5.987207285	2.224	2.328133	4.68224
15.	948.38	917.6397	3.241348405	2.43	2.328178	4.19021
16.	950.62	917.6623	3.466968926	2.32	2.327976	0.34379
17.	817.84	864.1133	5.657989338	2.83	2.550925	9.86131
18.	897.8	917.626	2.208286924	2.29	2.328133	1.6652
19.	827.89	905.5952	9.385932914	2.589	2.334749	9.82043
20.	814.54	824.1103	1.174933091	3.19	2.950842	7.49712
21.	961.93	1032.57	7.343569698	1.799	1.676196	6.82624
22.	997.56	910.3442	8.742912707	2.357	2.539592	7.7468
23.	987.8	935.6451	5.279904839	1.5	1.441329	3.9114
24.	846.98	920.7319	8.707631821	2.7	2.790991	3.37004
25.	863.27	934.7606	8.281371993	2.79	2.591288	7.12229
26.	928.76	934.4588	0.613592317	3.03	2.775812	8.38904
27.	973.52	936.0072	3.853315802	1.85	2.007869	8.53346
28.	792.18	801.8031	1.214761797	2.24	2.395983	6.96353
29.	973.52	935.9615	3.858010108	1.734	1.900612	9.60854
30.	957.37	945.5005	1.239802793	2	2.072189	3.60945

31.	990.22	945.5431	4.511815556	1.66	1.812105	9.16295
32.	1100.85	1007.737	8.458282236	1.407	1.464275	4.07072
33.	824.51	901.6995	9.36186341	2.47	2.290825	7.25405
34.	939.56	994.4436	5.84141513	2.8	2.675803	4.43561
35.	922.4	935.3498	1.403924545	2.201	2.289308	4.01218
36.	1035.93	935.261	9.717741546	1.564	1.664572	6.43043
37.	831.3	810.1688	2.541946349	2.456	2.338733	4.77471
38.	907.89	935.3346	3.02289925	2.56	2.389102	6.6757
39.	833.01	809.8445	2.780939004	2.8	3.039874	8.56693
40.	824.51	904.8245	9.740876399	3.01	2.977295	1.08654
41.	928.76	935.3498	0.709526681	2.23	2.289308	2.65955
42.	968.85	945.561	2.403777675	2	2.072016	3.6008
43.	1049.38	1007.335	4.006651547	1.863	1.764602	5.2817
44.	961.93	935.9512	2.700695477	1.99	2.087394	4.89417
45.	922.4	994.4593	7.812153079	2.65	2.475247	6.59445
46.	1138.06	1073.7	5.655237861	1.35	1.448092	7.26607

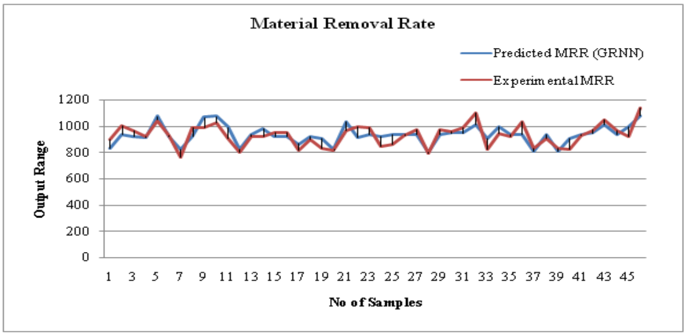

Figure 17: Comparison of Experimental and Predicted MRR for Copper Iron Alloy

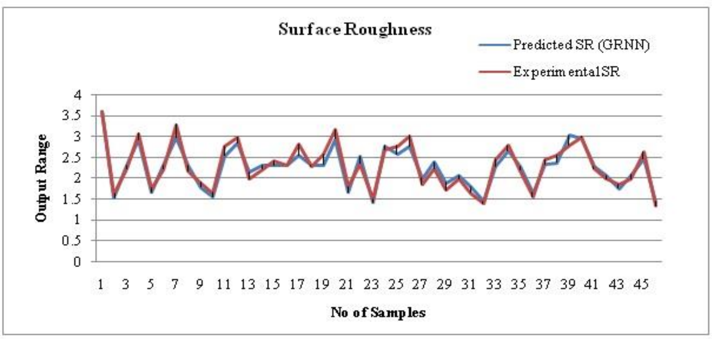

Figure 18: Comparison of Experimental and Predicted SR for Copper Iron Alloy

The Table 4 shows the errors between the experimental and predicted values for MRR and SR using G for Lead Tin Alloy. The comparison between the experimental values and predicted values of MRR and SR using G of Lead Tin alloy is shown in Figure 19 and Figure 20.

Table 4: Output Value of MRR and SR Through G for Lead Tin Alloy

Sl.No.	Experimental MRR (mm^3/min)	Predicted MRR(mm^3/min)	Error MRR	Experimental SR(μm)	Predicted SR(μm)	Error SR
1.	1709	1785.191	4.45822118	2.45	2.209145	9.83082
2.	2014.86	1983.379	1.56244106	1.415	1.498477	5.89943
3.	1970.09	2090.663	6.12017725	1.624	1.78553	9.94643
4.	1916.85	2016.638	5.20583249	2.2	2.027944	7.82073
5.	2182.26	2005.522	8.09885165	0.788	0.7723	1.99239
6.	1997.84	1950.596	2.36475393	1.609	1.745509	8.48409
7.	1688.65	1787.283	5.84093803	2.109	1.959655	7.08132
8.	1997.84	1951.471	2.32095663	1.52	1.661969	9.34007
9.	2085.98	2158.54	3.47846096	1.201	1.176902	2.00647
10.	2149.19	2015.516	6.2197386	0.801	0.772334	3.57878
11.	1896.34	1996.7	5.2922999	2.1	1.927996	8.19067
12.	1746.88	1787.438	2.32173933	1.905	1.958929	2.83092
13.	1943.11	1982.853	2.04532939	1.887	1.700982	9.85787
14.	2009.16	1950.596	2.91484999	1.571	1.685509	7.28892
15.	1948.44	1999.493	2.62019872	1.53	1.485469	2.91052
16.	2003.48	1950.49	2.64489788	1.709	1.785454	4.47361
17.	1751.19	1787.438	2.06990675	1.9	1.958929	3.10153
18.	2003.48	1950.596	2.63960708	1.566	1.685509	7.63148
19.	1842.16	1949.7	5.83771225	1.91	1.789051	6.33241
20.	1751.19	1787.445	2.07030648	1.899	1.958881	3.15329
21.	2136.25	2165.715	1.37928613	1.211	1.273694	5.17704
22.	1891.29	1927.536	1.91646971	1.999	1.924443	3.72971
23.	2055.75	1984.13	3.48388666	1.431	1.516065	5.94444
24.	1866.4	1966.153	5.34467424	2.013	1.887854	6.21689
25.	1842.16	1966.163	6.73139141	1.945	1.787909	8.07666
26.	1916.85	1943.313	1.38054621	2.008	1.824438	9.14153
27.	1970.09	1967.14	0.14973935	1.5	1.58532	5.688
28.	1800.08	1733.842	3.67972535	1.789	1.867909	4.41079
29.	1937.8	1967.116	1.51284962	1.699	1.685333	0.80441
30.	2049.81	1983.562	3.2319093	1.707	1.620212	5.08424
31.	2009.16	1983.576	1.27336797	1.5	1.620078	8.0052
32.	2142.69	2045.98	4.51348539	0.62	0.678726	9.47194
33.	1866.4	1966.135	5.34370982	1.934	1.787866	7.55605
34.	1916.84	1943.306	1.38070992	2.309	2.124462	7.99212
35.	2014.86	1966.641	2.39316876	1.597	1.686576	5.60902
36.	2162.3	2045.818	5.38694908	0.8	0.871223	8.90287
37.	1800.08	1732.054	3.77905426	1.9	2.007612	5.66379
38.	2020.6	1966.637	2.67064238	1.704	1.686527	1.02541
39.	1768.66	1731.758	2.08643832	2.102	2.008317	4.45685

40.	1842.16	1943.164	5.48291136	2.345	2.124662	9.39608
41.	2020.6	1966.641	2.67044442	1.64	1.686576	2.84
42.	2079.86	1983.594	4.62848461	1.634	1.620005	0.85649
43.	2162.3	2105.895	2.60856495	0.881	0.950873	7.9311
44.	1970.09	1967.116	0.15095757	1.539	1.685267	9.50403
45.	1922.04	1943.309	1.10658467	1.997	1.824226	8.65168
46.	2223.3	2153.135	3.15589439	0.8	0.863019	7.87737

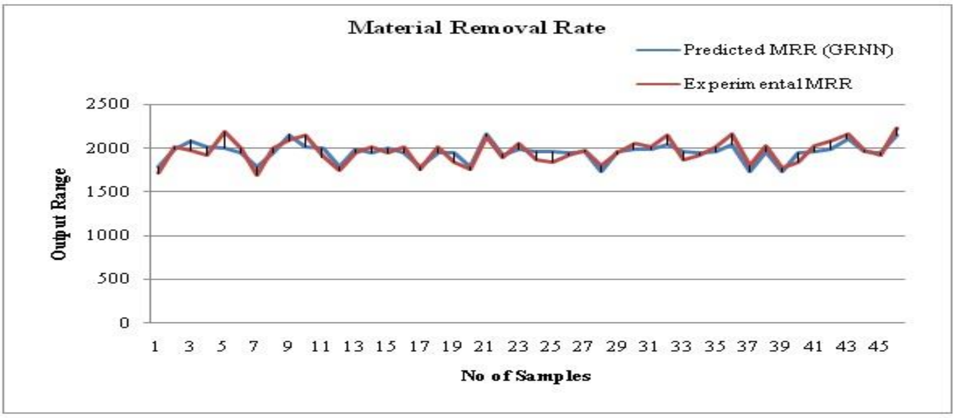

Fig. 4.23: Comparison of Experimental and Predicted MRR for Lead Tin Alloy

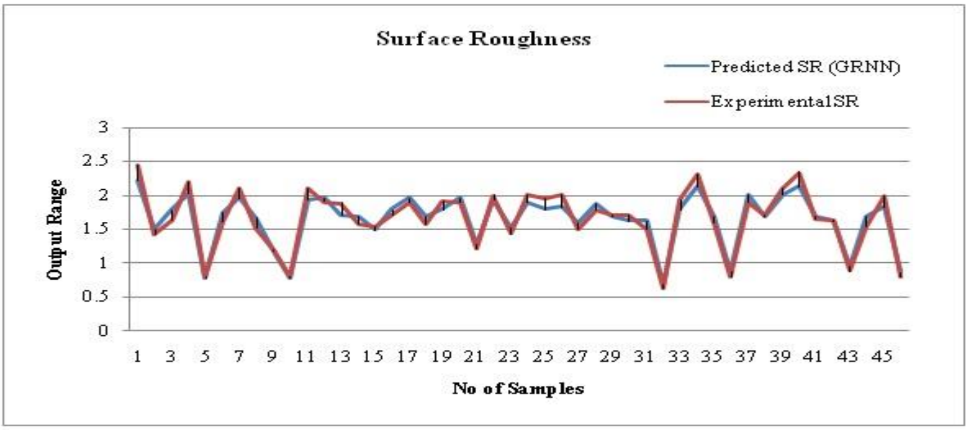

Fig. 4.24: Comparison of Experimental and Predicted SR for Lead Tin Alloy

4. Conclusion

✓ AWJM Process Optimization for Alloys: The study has demonstrated the potential of Abrasive Water Jet Machining (AWJM) for optimizing cutting parameters like pressure, abrasive flow rate, and orifice diameter for non-ferrous alloys such as Aluminum 6061, Copper-Iron, and Lead-Tin. AWJM offers versatility and minimal thermal distortion, making it suitable for these alloys.

✓ Prediction Accuracy of RNN Models: The Regression Neural Network (RNN) models effectively predicted material removal rates (MRR) and surface roughness (SR) for all three alloys with a close approximation to experimental values. The models achieved an average prediction error of less than 10%, which validates their efficiency for this machining process.

✓ Influence of Key Process Variables: Increasing the abrasive flow rate consistently resulted in higher material removal rates, while increasing the orifice diameter reduced the MRR and increased surface roughness. These findings highlight the importance of precise control over these variables to optimize AWJM outcomes.

✓ Advantages and Limitations of RNN: The RNN model demonstrated fast learning and reliable predictions, without needing iterative processes. However, determining the optimal smoothing factor remains a challenge, which can affect the model's accuracy in certain scenarios.

✓ Experimental vs Predicted Values: Across the alloys, predicted values for both MRR and SR were closely aligned with experimental results. The models provided significant insights into how different parameters influence cutting performance, supporting their use in machining optimizations.

✓ Potential for Future Work: The research opens avenues for further investigations into other process parameters and materials. Future research could focus on enhancing the accuracy of predictions and exploring additional optimization methods for broader applications in complex material machining.

Conflict of interest

There is no conflict of interest in the submission of this work, and has been agreed by all the authors for the publication of the manuscript.

Credit Author Statement

E.Srimathi - Investigation

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Itha Veeranjaneyulu - Formal Analysis.

M. Ravichandran - Writing - review & editing.

G.Senthilkumar - Writing - review & editing

K. S. Raghuram - Writing - review & editing

I. John Solomon - Methodology, Conceptualization, Original drafting (corresponding author)

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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